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Abstract

This paper describes the introduction of stochastic linear programming into Operations DER-CAM, a tool used to obtain optimal operating schedules for a given microgrid under local economic and environmental conditions. This application follows previous work on optimal scheduling of a lithium-iron-phosphate battery given the output uncertainty of a 1 MW molten carbonate fuel cell. Both are in the Santa Rita Jail microgrid, located in Dublin, California. This fuel cell has proven unreliable, partially justifying the consideration of storage options. Several stochastic DER-CAM runs are executed to compare different scenarios to values obtained by a deterministic approach. Results indicate that using a stochastic approach provides a conservative yet more lucrative battery schedule. Lower expected energy bills result, given fuel cell outages, in potential savings exceeding 6%.

Keywords: Batteries, Optimal Scheduling, Smart grids, Stochastic Systems, Uncertainty, Microgrids.

Introduction

The microgrid concept has recently gained significant attention from academia, equipment vendors, and energy companies alike. A microgrid can be defined as a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid, and can connect and disconnect from the grid, enabling it to operate in both grid-connected and islanded-modes [1]. Microgrids can contribute to ensure reliable, low cost, and environmentally friendly energy by taking advantage of distributed energy resources (DER) (including renewable sources), small-scale yet efficient fossil-fired combined heat and power technology (CHP), and both mobile and stationary storage technologies [2–4]. Furthermore, microgrids can provide locally high power quality and reliability (PQR) to sensitive loads and/or critical infrastructure [5]. By increasing the number of supply sources, microgrids are prone to a high degree of operational complexity, particularly when storage technologies are used under time dependent energy tariffs and peak pricing [6,7]. Because loads are inevitably quite variable in small systems, it is crucial to tightly control sources so that loads are reliably served, particularly under uncertainty and if islanded operation is a goal.

The microgrid planning and scheduling problem has been previously addressed using different approaches. Most models found in the literature use linear or mixed integer linear programming [8–11], while a few adopt nonlinear programming [12,13]. However, little work has been published considering uncertainty [14,15], suggesting a need for the contributions introduced with this work.

This paper follows on previous work on the problem of optimal scheduling of a reconfigurable (4 MWh-1 MW or 2 MWh-2 MW) lithium-iron-phosphate (LFP) battery, considered for use at the Santa Rita Jail (SRJ), given the output uncertainty of a legacy fuel cell [16].

This almost 3 MW peak facility is located in Dublin, California, and houses up to 4500 inmates. During the past decade, it has installed a series of efficiency and DER technologies to reduce its energy consumption, including a 1.2 MW rooftop photovoltaic (PV) system and a 1 MW molten carbonate fuel cell (MCFC) operating as a CHP unit [16]. The fuel cell has proven unreliable and is frequently out of service. These assumed random outages combined with time variable tariffs for both energy and power demand incurs significant potential financial penalties [16]. Fuel cell outages result in increased utility electricity purchases, significantly higher peak power demand charges, and losses of heat supply replaced by natural gas purchase. Please note that heat loads are not explicitly addressed in this work, so all natural gas purchases are tied to MCFC generation and not to replace its foregone waste heat. In part to mitigate this unreliability problem, the Jail has added local electrical storage in the form of an LFP battery.

This paper adds to previous work by expanding on the Operations version of the Distributed Energy Resources – Customer Adoption Model (Operations DER-CAM) by introducing stochastic linear programming and introducing uncertainty in MCFC availability, which determines an adjusted battery schedule.

DER-CAM [17], is a mixed integer linear programming algorithm (MILP) developed at the Lawrence Berkeley National Laboratory (LBNL) written and implemented in GAMS. It has two main versions that may be used to size and/or schedule the optimal DER capacity for a given site: 1) I+P-DER-CAM (Investment and Planning) picks optimal microgrid equipment combinations and the corresponding dispatch, based on 36 or 84 typical days representing a year of hourly energy loads and technology costs and performance, fuel prices, existing weather data, and the utility tariff; 2) Operations DER-CAM as applied in this study is used for the optimization of the detailed dispatch in a microgrid for a given period, typically a week ahead, with a time resolution of 5 min, 15 min, or 1 h, assuming the installed capacity is known, and using weather forecasts from the web to forecast requirements.

Modeling

Stochastic programming

To date, only deterministic methods have been applied within DER-CAM, i.e., assuming all loads and operational parameters are known. In this work, the uncertainty in MCFC availability is added to Operations DER-CAM, which requires a stochastic approach to the problem. Unlike the I+P version, Operations DER-CAM is used in situations where the microgrid configuration is known and the algorithm is used to optimize dispatch, typically on a week-ahead basis, using the time step most relevant to the economics, typically 15 min.

The enhancements now introduced are accomplished by using a stochastic linear programming method, with the problem modeled as having general recourse [18,19]. This is a standard approach wherein variables are split into different stages, referring to different moments of decision. In this particular case, two stages are considered and the distinction is made depending on whether or not their values must be known before any scenario occurs. Variables that do not depend on scenarios are first stage variables, and the ones that do are second stage variables that reflect the uncertainty in the problem. Stochastic linear programming is a well-known approach for scheduling problems, with a wide range of applications. In [20], two-stage stochastic programming is used to deal with scheduling problems of chemical batch processes, while in [21] a stochastic programming approach with disruption scenarios is used for vehicle scheduling in public transport. Applications to energy systems can also be found, e.g. in [22], where two-stage stochastic programming is used to develop offering strategies for wind power production while considering the uncertainty in wind power and market prices. In [23], two-stage stochastic mixed-integer linear programming is used to design time-of-use (TOU) rates to deal with demand response options.

Battery scheduling problems can also be found in the literature, namely in [24], where a deterministic MILP program is developed to schedule battery charging by a set of PV arrays on a space station. In [25], the collective discharge scheduling problem is addressed using a decision-making algorithm, while in [26] charge and discharge strategies are used to study the sensitivity of electric vehicle battery economics.

In the application presented here, a schedule for the LFP battery is needed on a week-ahead basis, without knowing MCFC availability. This means that charging or discharging the battery must be planned before knowing whether the MCFC will be generating, and these will be the first stage variables of the problem. Other variables, such as electricity purchases, will depend on whether or not the MCFC is running, and will therefore take different values in different scenarios, making them second stage variables.

The virtue of using this stochastic approach is that all scenarios are explicitly considered in the model, meaning the first stage variables will be determined minimizing the expected losses of all scenarios against the solution found.

This approach allows the LFP battery scheduling to be calculated accounting for the uncertainty in the future MCFC output, and thereby balancing the potential outcomes that may occur; that is, if the MCFC availability is uncertain, an LFP battery schedule is required that minimizes the expected energy cost regardless of the MCFC availability that actually transpires. Under this stochastic approach, the problem can be described as:

$$\min c_1^{\intercal} x_1 + E[f(x_1, \tilde{\omega})] \tag{1}$$

$$s.t. \qquad x_1 \geq 0 \tag{2}$$

Where x_1 represents all first stage decision variables, determined prior to the realization of any uncertain scenario. In the stochastic formulation of Operations DER-CAM now adopted, such variables include battery input and output decisions (charging and discharging over time). This subset of x_1 describing the LFP charging and discharging decisions in each of the 672 timesteps (15 min resolution over 7 days), and how it differs from the second stage equivalents are the key point of interest in this work. All other variables assumed scenario-independent are also included. In this case, the electricity production from the PV array is treated as known. Many sources of uncertainty may exist, and PV output is clearly one of them. They are not addressed here because fuel cell uncertainty has a stronger influence on costs at this reliable solar site. Further, while the existing PV array is rated at 1.2 MW, in practice its peak output is far short of this level, making the MCFC a more critical resource (see Figure 1). In this formulation, c_1 represents the cost coefficient vector of first stage variables, and $E[f(x_1, \tilde{\omega})]$ is the expected value of the second stage problem, where second stage variables are calculated for each specific data scenario ω. Here, $\tilde{\omega}$ is a discrete random variable defined over probability space (Ω, P), with $p_\omega = P\{\tilde{\omega} = \omega\}$ for each scenario $\omega \in \Omega$.

The generic formulation of the second stage problem, also known as the recourse sub problem, is written as:

$$f(x_1, \omega) = \min c_2^{\intercal} x_{2,\omega} \tag{3}$$

$$s.t.$$

$$A_1 x_1 \leq b_1 \tag{4}$$

$$A_{2,\omega} x_{2,\omega} + B_1 x_1 \leq b_{2,\omega}\ , a_\omega \in b_{2,\omega} \tag{5}$$

$$x_{2,\omega} \geq 0 \tag{6}$$

Where $x_{2,\omega}$ represents all second stage decision variables in each scenario ω, including the subset of uncertain fuel cell operation variables, electric utility purchases and sales, CO_2 emissions, among all other variables that depend on the scenario outcome. Here, c_2 represents the cost coefficient vector of second stage variables.

Similarly to variables, the constraints in this formulation are divided depending on to which stage they apply. Constraints related only to first stage variables, such as LFP battery operational constraints, are modeled by matrix A_1 and vector b_1, whereas all other constraints, such as energy or heat balances, that may involve both first stage and second stage variables are represented by matrices $A_{2,\omega}$ and B_1 and vector $b_{2,\omega}$. Since the power output of the fuel cell is limited by its uncertain availability, a_ω, this type of constraint falls in the category described by equation 4. Generically speaking, since the MCFC generation is a second stage variable we will have $\text{MCFC Generation}_\omega \in x_{2,\omega}$ and $\text{MCFC Generation}_\omega \leq a_\omega$.

If the random variable $\tilde{\omega}$ is a discrete random variable, the stochastic problem can be rewritten in a deterministic equivalent program. In this case, the expected value of the second stage problem becomes:

$$E[f(x_1, \tilde{\omega})] = \sum_\omega p_\omega f(x_1, \omega) \tag{7}$$

And the problem is now written as:

$$\min c_1^T x_1 + \sum_\omega p_\omega c_2^T x_{2,\omega} \tag{8}$$

$$\text{s.t.}$$

$$A_1 x_1 \leq b_1 \tag{9}$$

$$A_{2,\omega} x_{2,\omega} + B_1 x_1 \leq b_{2,\omega}\ , a_\omega \in b_{2,\omega} \tag{10}$$

$$x_{2,\omega} \geq 0 \tag{11}$$

It will be clarified when describing the runs performed that the number of scenarios being considered in this paper is finite (three scenarios in each set) with discrete probability distributions, making the use of the deterministic equivalent problem a valid approach. The number of scenarios is kept small with the aim of capturing only the most important events. The overall aim is to construct a set of scenarios of optimistic, expected, and pessimistic situations [27].

DER-CAM Implementation

The implementation in DER-CAM of the recourse model is now presented. Please note that although an overview is given to illustrate all changes required, the extent of formulation presented is kept to a minimum. The full mathematical description of DER-CAM is available in [28] and contemplates all different restrictions that establish, for example, the relations between costs and energy consumption, whereas here they are merely identified using the notation $variable_i(variable_j, parameter_k)$ to specify that $variable_i$ is a function of $variable_j$ and $parameter_k$.

Additionally, the case study presented here forces the options used in the optimizations to be tailored to its needs. Although the full stochastic implementation is introduced, some features will not be showcased in the runs. These include the environmental objective function, electricity sales, and all heat related parts of the model.

Finally, the stochastic programming implementation was made so that some DER technologies can be set to "deterministic" while others are "stochastic", i.e., the user can specify if the technology has predictable or scenario-dependent output (such as the MCFC).

Parameters:

EL electric loads

HL	heat loads
Ld	min. output from deterministic DER
Ls	min. output from stochastic DER
NM	misc. NG loads (e.g. cooking)
p_ω	probability of scenario ω occurring
Ud	max. output from deterministic DER
Us_ω	max. output from stochastic DER

First stage variables:

EPB	electricity provided by the battery
EGd	electricity provided by deterministic DER
ESd	electricity sold by deterministic DER
HGd	heat from deterministic DER
$eGd(EGd, ESd)$	CO_2 emissions from det. DER
$eM(NM)$	CO_2 emissions from miscellaneous NG loads
$cNGGd(EGd, ESd)$	NG costs for deterministic DER
$cNGed(EGd, ESd)$	CO_2 tax costs for deterministic DER
$cNGM(NM)$	cost of NG miscellaneous loads
$cVd(EGd)$	var. maintenance costs of deterministic DER
ESB	electricity stored in the battery
$Sd(ESd)$	sales from deterministic DER

Second stage variables (by scenario ω):

$eGs_\omega(EGs_\omega, ES_\omega)$	CO_2 from stochastic DER (i.e. fuel cell)
$eU_\omega(EU_\omega)$	CO_2 from electricity purchase
$cEe_\omega(EU_\omega)$	CO_2 tax utility electric costs
$cEV_\omega(EU_\omega)$	volumetric electric costs

$cEP_{\omega}(EU_{\omega})$ electric power demand costs

$cNGes_{\omega}(EGs_{\omega}, HU_{\omega}, ES_{\omega})$ CO_2 tax for stochastic DER.

$cNGGs_{\omega}(EGs_{\omega}, ES_{\omega})$ NG costs for stochastic DER

$cNGH_{\omega}(HU_{\omega})$ utility NG costs for heating

$cVs_{\omega}(EGs_{\omega})$ variable maintenance costs of stochastic DER

EGs_{ω} electricity from stochastic DER

EU_{ω} electricity provided by the utility

ESs_{ω} electricity sold from stochastic DER

HGs_{ω} heat provided by stochastic DER

HU_{ω} heat provided by the natural gas from the utility

$Ss_{\omega}(ES_{\omega})$ electricity sales from stochastic DER

Financial objective function, C:

$$\min \mathrm{C} = \mathrm{cNGGd} + \mathrm{cNGed} + \mathrm{cVd} + \mathrm{cNGM} - \mathrm{Sd} \tag{12}$$
$$+ \sum_{\omega} p_{\omega} (cEV_{\omega} + cEP_{\omega} + cEe_{\omega} + cNGGs_{\omega} + cNGH_{\omega} + cNGes_{\omega} + cVs_{\omega} - Ss_{\omega})$$

Environmental objective function, E:

$$\min \mathrm{E} = \mathrm{eGd} + \mathrm{eM} + \sum_{\omega} \mathrm{p}_{\omega} (\mathrm{eGs}_{\omega} + \mathrm{eU}_{\omega}) \tag{13}$$

Subject to:

Electricity balance

$$\mathrm{EL} + \mathrm{ESB} + \mathrm{ESd} + \mathrm{ESs}_{\omega} = \mathrm{EU}_{\omega} + \mathrm{EGs}_{\omega} + \mathrm{EGd} + \mathrm{EPB} \tag{14}$$

Heat balance

$$\mathrm{HL} = \mathrm{HU}_{\omega} + \mathrm{HGd} + \mathrm{HGs}_{\omega} \tag{15}$$

Operational constraints

$$\mathrm{Ld} \leq \mathrm{EGd} + \mathrm{ESd} \leq \mathrm{Ud} \tag{16}$$

$$\mathrm{Ls} \leq \mathrm{EGs}_{\omega} + \mathrm{ESs}_{\omega} \leq \mathrm{Us}_{\omega} \tag{17}$$

$$\mathrm{EC}, \mathrm{ESB}, \mathrm{EPB}, \mathrm{EGd}, \mathrm{ESd}, \mathrm{HGd} \geq 0 \tag{18}$$

$$\mathrm{EP}_{\omega}, \mathrm{EGs}_{\omega}, \mathrm{EU}_{\omega}, \mathrm{ESs}_{\omega}, \mathrm{HGs}_{\omega}, \mathrm{HU}_{\omega} \geq 0 \tag{19}$$

As mentioned before, this is only a brief overview of the revised mathematical formulation. Please note that Operations DER-CAM is a discrete time model that currently allows time-steps of 5 min, 15 min, or 1 h. All constraints presented here are valid in each time step, while the costs shown in the objective function are summed through the whole time period under analysis. The time index is omitted to simplify the formulation. For further detail, please refer to [28] or the authors.

Model Data

As mentioned, the model options used in this work were chosen according to the specific conditions of the Santa Rita Jail microgrid. For this application, an historic 15 min electricity load data set from a week, August 25 to 31, 2009, were used.

In the models created, electricity may be supplied to the SRJ microgrid directly by the utility, by a 1.2 MW rooftop PV array or by the 1 MW MCFC, subject to uncertain availability. According to its manufacturer's specifications, the conversion efficiency of the fuel cell is taken to be 35% (lower heating value). Additionally, the reconfigurable LFP battery can be used by the microgrid to offset energy and power costs and in this work only the 2 MWh-2 MW configuration is used[1]. According to the data available, the electric discharging efficiency of the LFP battery is estimated to be 83%, while it has a decay rate of 0.002% per hour.

Pacific Gas & Electric (PG&E) electricity and natural gas tariffs effective at the Jail were used [29]. For further reference on the data specifics please refer to [16].

[1] Ultimately, the Jail chose to adopt the 4 MWh/2 MW configuration

The following options were used in the GAMS models: iteration limit: 5 000 000; max resolution time: 3600s; optimality gap: 0.001; decimals: 8; threads: 2; using the CPLEX solver.

Case-study optimization

Basic SJR runs

Following a series of tests to ensure proper implementation of the code, some basic runs were made to better understand the scope of the problem. In these weeklong optimizations, no uncertainty was considered and both the LFP battery and MCFC were turned on and off to realize maximum potential bill savings from their use. Please note that the 1.2 MW PV array was assumed to be perfectly predicted.

Key results

The results obtained in these runs, summarized in Table 1, offer some relevant conclusions; namely, relations between time dependent energy charges (time-of-use) and power demand costs under four possible availability states, as well as the contributions from the local utility, the MCFC and the LFP battery, as well as its average state of charge (SOC) during the optimization period. As seen in run B1, where both the battery and the fuel cell are disabled, the microgrid is forced to meet all its electricity needs by PV and PG&E purchases. Due to tariff and load specifics, demand charges represent more than 60% of the week's total energy costs[2]. This illustrates the potential for DER to lower the electricity bill, and as seen in run B2, the battery alone allows weekly savings of over $6200, reflected mostly in demand cost reductions, even though 1515 kWh additional utility purchases are needed for charging purposes, as seen in the difference between utility purchases from runs B1 to B2.

[2] Note that it is assumed the monthly peak demand occurs in the test week, which is why demand charges represent such a huge part of the week's bill.

The MCFC has a significant impact on both energy and demand costs, although the later represents a much more relevant contribution to the overall MCFC financial benefit. Please note that when using the MCFC all fuel costs are also being considered, but as the recovered heat is not considered in this study, the total savings could be higher. These results also illustrate why fuel cell outages can be so costly in the SRJ microgrid. Due to low energy purchase requirements the MCFC operation orients towards reducing demand charges, which are unlikely to be correctly considered in any fixed scheduling, whether or not outages are taken into account.

Finally, when making both the LFP battery and the MCFC available and 100% reliable (B4), savings are maximized, as expected, with a total energy cost reduction over 30%, from $75411 to $52203. In this case, the electricity generated by the MCFC is higher than in B3, where the LFP battery is unavailable, suggesting that besides meeting the electricity load, the fuel cell is also used to charge the battery. This favors the further use of the fuel cell beyond the additional LFP battery charging, as can be noted when comparing the MCFC output to B3. This example showcases one of the advantages of using an integrated model such as DER-CAM to capture indirect effects and assuming additive behavior would be misleading.

The simultaneous use of the LFP battery and the MCFC does not correspond to adding their individual effects. This can also be observed comparing the savings obtained in the runs.

The detailed scheduling obtained in run B4 is illustrated in Figure 1, where it must be highlighted that utility purchases are kept mostly to a flat profile, affected mainly by the PV array output. As demand charges represent a significant share of the total energy costs, keeping purchases as flat as possible is the natural solution to minimize electricity costs, particularly in time periods where prices are higher. In this case, the battery is also used to offset high power and time-of-use charges, assuming the monthly peak occurs in this week, i.e. on day 4 (Friday, 8-28-2009), while the average SOC is kept to 24.5%. Note that the battery is left at its minimum charge level most of the time. Since using the battery incurs losses, it should only be used when the benefit exceeds those losses.

MCFC availability scenarios

Following the initial set of runs, a second set was made to test DER-CAM's new stochastic capabilities. Here, the B4 run from the first set was used as reference, as it represents the behavior one would expect when the LFP battery is available without outages. If fuel cell availability is assumed always at the rated capacity of 1 MW, optimal utility purchases can be minimized and financial savings maximized.

Scenario description

This second set of scenarios have hypothetical high, medium and low fuel cell availability, $\omega = \{h, m, l\}$. In each scenario, fuel cell maximum power output in each 15 minute time steps was generated randomly, using the following assumptions.

If we let $a_{t,\omega} \in A$ be the maximum output available from the MCFC during time step t in scenario ω, and R be the rated nameplate capacity, the probability mass functions used to characterize the discrete probability distributions of random variable A are:

$$f_A(a_{t,\omega}) = P(A = a_{t,\omega}) \tag{20}$$

$$f_A(a_{t,h}) \begin{cases} 0.45, a_{t,h} = R \\ 0.35, a_{t,h} = 0.75R \\ 0.15, a_{t,h} = 0.50R \\ 0.05, a_{t,h} = 0.25R \\ 0.00, a_{t,h} = 0 \end{cases} \tag{21}$$

$$f_A(a_{t,m}) \begin{cases} 0.25, a_{t,m} = R \\ 0.25, a_{t,m} = 0.75R \\ 0.25, a_{t,m} = 0.50R \\ 0.15, a_{t,m} = 0.25R \\ 0.10, a_{t,m} = 0 \end{cases} \tag{22}$$

$$f_A(a_{t,l}) \begin{cases} 0.05, a_{t,l} = R \\ 0.15, a_{t,l} = 0.75R \\ 0.30, a_{t,l} = 0.50R \\ 0.25, a_{t,l} = 0.25R \\ 0.25, a_{t,l} = 0 \end{cases} \tag{23}$$

This creates availability profiles where only 4 output states are possible, each with associated probabilities. In these random scenarios no time-dependency exists between consecutive time steps. This means that the maximum available MCFC output can go from zero to 1 MW and then back to zero in three consecutive 15 min time steps, which is highly unrealistic. This can be handled in DER-CAM using appropriate operating constraints, but for the purpose of testing the implementation of the stochastic method they were not used.

Following a deterministic method, each of the scenarios $\omega = \{h, m, l\}$ was run separately (M1, M2 and M3), followed by calculating the mean of all results obtained, thus representing the expected value of the deterministic approach.

A stochastic MS run was then made, with all three scenarios simultaneously used with equal probability, allowing a comparison between both methods. Results obtained in this second set of runs are found in Table 2.

In order to better understand these results it is important to stress that the scenarios generated contain only information on the maximum available power output from the MCFC in a given time step. As seen in Figure 1, even in a full availability scenario the fuel cell is not always working at full capacity.

This is due to the economic balance that results from considering the local tariff structures, as well as other available sources, such as the PV array, and the actual SRJ load. Thus, even if the MCFC is fully available in a given time step, it still needs to be economically attractive to use. Conversely, it may occur that using the fuel cell would be economically desirable while it is unavailable. This explains why when looking at results from different scenarios, the differences found in generation may not always be as significant as those in the availability profiles. Also, it must be noted that in practice, the MCFC will be subject to all sorts of operating constraints, such as part load efficiency and ramp rates that might make these schedules unrealistic.

Key results

Analyzing the results shown in Table 2, a first conclusion may be that regardless of the availability scenario, the total energy costs are always higher than in the B4 run, with increases ranging from 5% in M1 to almost 20% in M3. This is an expected result, as all M1 to M3 runs have periods of limited availability, but relevant nonetheless, as it stresses the need to consider the MCFC outages to avoid underestimating energy costs. Likewise, utility purchases increase as the MCFC availability decreases, and this leads to higher power costs, representing approximately 40% of total costs in the B4 run, but 45% in M1 and over 55% in M3.

As for the battery, the average SOC increases significantly as the fuel cell is less available, going from an average state of charge of 28% in M1 to over 46% in M3, followed by a similar increase in the electricity provided. This result highlights how the MCFC availability can potentially impact the LFP scheduling and usage at the SRJ microgrid.

It is relevant to point out that in this particular aspect the results between M2 and M3 are not as different as one might expect, but as explained, this is due to the definition of the availability profiles. In this case, the MCFC generation both in M2 and M3 reaches levels low enough that the LFP battery results become closer to the ones in B2 and both the average SOC and battery output in M2 and M3 are similar.

When analyzing the results obtained from the stochastic run, MS, it is clear that using this approach provides different results from those obtained by the deterministic method. Namely, the total energy costs obtained in MS are similar to those obtained in the lowest availability scenario, M3, while the Average of M1 to M3 is very close to the result in the medium availability scenario, M2. This indicates that using the stochastic approach provides a battery scheduling that is typically more conservative than calculating the average of all individual scenarios. This is due to the fact that in the stochastic model all three scenarios are deemed possible, and therefore, first stage variables like the battery scheduling are estimated to minimize the impact of all possible outcomes, which is not true when calculating the average of each deterministic individual scenario. While the stochastic approach does not provide a lower expected energy cost, it reduces the risk of financial losses.

In fact, using the stochastic approach in MS provides the microgrid operator with a single battery schedule, while the deterministic approach gives a different schedule for each scenario (or one average schedule), forcing the operator to make a choice between them.

Assuming a deterministic approach, if for instance the LFP battery schedule given by the high availability scenario is adopted and the MCFC experiences outages described by the low availability scenario, significant financial losses are to be expected, particularly due to demand charges.

In this case losses are higher than the simple difference between the total energy costs of M1 and M3. This is due to the fact that the low availability scenario assumes a high battery usage to mitigate demand charges, and if the scheduling from the high availability scenario is adopted, the battery may not have been previously charged, forcing the microgrid to buy electricity from the utility in the event of an outage at whatever price prevails. Thus, using this deterministic approach, the total energy costs would actually be higher than those in M3. Additional remarks on this issue are made later on when analyzing the runs based on historic MCFC data.

A particularly interesting result to corroborate this finding is the high average state of charge (52.2%) found in the proposed MS battery schedule, which once more suggests a more conservative battery scheduling compared to the average of M1 to M3.

Historic data

Following the process described above, a second set of MCFC availability scenarios was tested. As the major goal of this paper is to optimize the battery scheduling under real observed uncertain availability of the MCFC, it is of interest to do this by considering past failure behavior.

While in the previous set of scenarios the MCFC availability profiles were artificially designed to force high, medium and low availability scenarios so that the stochastic capabilities added to DER-CAM could be tested, it is now necessary to generate MCFC availability scenarios that follow the actual behavior of the SRJ microgrid, regardless of what this means in terms of the MCFC being always (or never) available.

Scenario description with Markov Chains

To generate MCFC availability profiles for this set, historic data of its power output were used. These data are available in 15 minute intervals from 2007 to 2010. In this work, data from 2010 were analyzed and used to model output availability as a Markov chain. The sample used for this purpose contained over 33 000 output values.

In addition to providing estimates based on historic data, this approach also addresses the serious limitation of assuming a random outage pattern, i.e. it solves the lack of time-dependency. In fact, by modeling the historic behavior of the fuel cell this way, the output in any given time step depends on what happened previously.

Markov Chains are often used to describe processes wherein a transition occurs between two states [30] and the probability of transitioning to a certain state is only dependent on the previous state. Using a standard formulation:

$i \in I = \{1,2,\dots,r\}$ state space

$t \in T = \{0,1,\dots k\}$ time steps

$X(t)$ state of the system at time t

In this case, $P_i(t) = P(X(t) = i)$ is the probability that the system is in state i at time t.

Now, assuming a single step transition, a process is said to have the Markov Property if the conditional probability that the system will be in state j at time t, given that it is in state i at time $t-1$ is independent of all other past events:

$$P_{ij}(t) = P(X(t) = j | X(t-1) = s,\ X(t-\alpha) = i) = P(X(t) = j | X(t-1) = s),\ \forall\ 0 \le \alpha < t-1$$

In other words, the process can be said to have the Markov property if, once the present state $X(t-1)$ is known, the future state $X(t)$ is independent of anything that happened in the past $X(t-n), n > 1$.

Analyzing the historic fuel cell output data, the 9 following states were identified (Table 3), illustrating how variable the MCFC output can be:

The historic data were converted to these output states using a filtering algorithm developed for this purpose, which addresses the fact that actual output values occur within a certain vicinity of the identified states, but also the fact that in a Markov Chain state changes take exactly one time step to occur. As this does not correspond to the real startup or shutdown fuel cell periods, an auxiliary “in transition” state was used. The period spent in this auxiliary state was then assigned to the adjacent state corresponding to the lowest power output. In other words, whenever the power output in the historic data went from state i to state j, and this transition took t time steps to happen, that period was identified as time "in transition" and was re-assigned to either i or j, depending on which of these states corresponded to the lowest output value. While this is a conservative approach and other options could have been taken, it assures that the output is never overestimated. Analyzing the historic and filtered data simultaneously, however, it becomes clear that the used method produces a very good approximation (Figure 2).

Using this data set, a second algorithm was then used to analyze state transitions and create the transition matrix where all transition probabilities are described by $P_{ij}(t)$ (Table 4). As seen in this table, transitions with state changes mostly occur from a running state to an outage (state 8), and generally the probability of remaining in a given state is very high.

Finally, a third algorithm was used to generate three availability scenarios, $\omega = \{\omega_1, \omega_2, \omega_3\}$, each of them assumes that the initial state was one of the three most commonly found states in the historic data set, $X_\omega(t_0) = \{8, 1, 5\}$, corresponding to an output of 0, 838, and 440 kW, respectively.

Key results

The results now obtained show a significant financial impact of MCFC outages (Table 5), in line with what has been verified at the SRJ site. In fact, in the deterministic method where all scenarios are tested separately, the total energy costs are higher than in the B4 run, with increases ranging from nearly 10% in H2 to almost 32% in H1. This again highlights the need for an accurate scheduling of the LFP battery, as it is noteworthy from the data presented in Table 5 that the power charges, where the battery can have its biggest impact, represent the largest share of total costs.

As for the results obtained in the stochastic run, HS, the total energy costs are similar to those obtained by the deterministic approach (average of H1 to H3), with both results nearing $62 000.

However, looking further into the results, important differences can be noted, namely on average LFP battery state of charge. In this case, the average SOC in HS is higher than that obtained in any of H1 to H3, and therefore also higher than the number obtained in the average scenario. This can be seen in Figure 3, where the detailed battery SOC is depicted for all considered scenarios. As observed, the SOC in the stochastic scenario is typically higher than the average of H1 to H3, suggesting a conservative scheduling that would lead to lower losses upon the realization of any of the H1 to H3 scenarios.

On this matter, it should be noted that as the stochastic model incorporates all scenarios simultaneously, the total energy costs obtained represent an expected value and not the actual energy cost once a given scenario occurs. Thus, the relevance of using this information comes from the fact that it explicitly incorporates uncertainty, which does not happen in the deterministic method. Additionally, using the stochastic method provides the microgrid operator with estimates for key variables such utility purchases depending on the scenario that occurs. This is valuable conditional information that is also not obtained in the deterministic approach.

To better illustrate this point, some additional runs were made. In this case, the battery schedule is assumed to be either that obtained by using the average of H1 to H3 or the one obtained in HS.

The electric loads were adjusted so that the total power requirement incorporates the battery input and output in each time step, thus artificially forcing the battery operation to follow the intended schedule.

Each availability scenario ω is then analyzed separately and the results obtained are shown in Table 6.

As mentioned, the information given by the stochastic method proved to be more reliable, as can be seen by comparing the results in C1 to C3 with the ones in HS. In fact, calculating the average of the total energy costs in C4 to C6 we obtain $62 372, which is exactly the total energy cost in HS. Doing the same for C1 to C3, however, yields $64 509, which is higher than the $62 089 obtained by averaging H1 to H3. This result is in line with what has been described when analyzing runs M1 to M3, and is a direct result of using the deterministic approach: being deterministic, a certain MCFC availability is assumed to occur and the LFP battery is scheduled exclusively for that availability profile. If the MCFC availability differs, not only will it impact electricity generation, but will also influence the utility purchases. In other words, the battery would not have been scheduled for an abnormal event. In practice, this can be observed by directly comparing the costs in H1 to C1, H2 to C2 and H3 to C3.

If the results obtained assuming the battery schedule follows the one provided by the stochastic method (C4 to C6) are then compared with those obtained with the LFP battery schedule from the deterministic method (C1 to C3), we see that savings are systematically achieved, particularly on power charges. Here, total weekly energy cost savings range from $1 170 to $3 781, representing over 6% of total costs. This suggests that using the stochastic method provides a conservative and more reliable battery schedule that minimizes the expected electricity bill given the uncertainty of the MCFC.

Conclusion

This paper analyzes the generic implementation of stochastic programming in Operations DER-CAM. Its use is illustrated by addressing the optimal scheduling of a reconfigurable LFP battery considered for installation in the Santa Rita Jail microgrid. The output uncertainty of a legacy 1 MW MCFC, which has often proven unreliable, justifies the Jail's interest in batteries.

Results are obtained from separately running deterministic scenarios and ones applying the stochastic approach. The implementation of stochastic linear programming followed the standard formulation of a two-stage recourse problem, and given the specific conditions of the problem under study the deterministic equivalent program was formulated.

Several sets of runs have been made. A few deterministic runs provide basic information on the range of costs obtainable by using the MCFC, or the LFP battery, or both together. Introducing uncertain MCFC availability in the DER-CAM model and comparing results obtained by the deterministic and stochastic methods demonstrates how uncertainty impacts the LFP scheduling.

Results indicate that the LFP schedule found by the stochastic method always outperforms the schedule given by the deterministic approach. Expected deterministic total weekly energy costs calculated this way exceed those calculated with the stochastic LFP schedule by $1170 up to $3781, depending on the scenario outcome.

Results indicate that using a stochastic approach can both increase the reliability of microgrid operations and improve its economic performance, which also illustrates the advantages of using an integrated modeling approach with a model such as DER-CAM.

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Table 1 – Basic runs. Weekly results summary.

Run	B1	B2	B1-B2	B3	B1-B3	B4	B1-B4	
LFP battery	No	Yes	savings	No	savings	Yes	savings	
MCFC	No	No		Yes		Yes		
Total energy costs (incl. Natural Gas)	$ 75 411	$ 68 905	$ 6 506	$ 57 345	$ 18 067	$ 52 203	$ 23 209	(31%)
Time-of-use charges	$ 27 740	$ 27 499	$ 242	$ 19 213	$ 8 527	$ 16 798	$ 10 943	
Power demand charges	$ 47 671	$ 41 407	$ 6 264	$ 27 324	$ 20 346	$ 20 699	$ 26 972	
Utility purchases, kWh	291448	292963		212308		184260		
MCFC generation, kWh	0	0		79140		107671		
Average battery SOC, %	0.0	38.9		0.0		24.5		
Battery output, kWh	0	7385		0		2353		

Table 2 – High, Medium and Low availability scenarios. Weekly results summary.

Run	B4	M1	M2	M3	Avg. M1:M3	MS	Observed fuel cell availability in MS
LFP battery	Yes	Yes	Yes	Yes	Yes	Yes	
MCFC	Yes	H	m	l	Avg.	h+m+l	
Total energy costs (incl. Natural Gas)	$ 52 203	$ 54 844	$ 58 689	$ 62 420	$ 58 651	$ 62 008	
Time-Of-Use charges	$ 16 798	$ 19 328	$ 23 380	$ 25 347	$ 22 685	$ 22 272	h
						$ 24 654	m
						$ 25 670	l
Power demand charges	$ 20 699	$ 24 447	$ 30 339	$ 34 625	$ 29 804	$ 29 518	h
						$ 35 064	m
						$ 37 824	l
Utility purchases, kWh	184260	211449	256987	275300	247912	247989	h
						272010	m
						279197	l
MCFC generation, kWh	107671	81061	36415	17980	45152	45341	h
						21321	m
						14133	l
Average battery SOC	24.5%	28.3%	45.1%	46.1%	39.8%	52.2%	
Electricity from the battery, kWh	2353	5176	9528	8936	7880	9175	

Table 3 – Output States

State	0	1	2	3	4	5	6	7	8
Output (kW)	890	838	736	636	537	440	227	68	0

Table 4 – Transition Matrix

Pij	0	1	2	3	4	5	6	7	8
0	0.9988	0	0	0	0	0	0	0	0.0012
1	0	0.9992	0	0.0001	0	0	0	0	0.0007
2	0	0	0.9980	0	0	0	0	0	0.0020
3	0.0003	0.0006	0.0003	0.9987	0	0	0	0	0
4	0	0	0	0.0003	0.9961	0	0	0	0.0036
5	0	0	0	0	0.0008	0.9971	0	0	0.0021
6	0	0	0	0	0.0106	0.0106	0.9681	0	0.0106
7	0	0	0	0	0	0	0.0079	0.9843	0.0079
8	0	0.0004	0.0005	0.0002	0.0011	0.0011	0.0002	0.0002	0.9963

Table 5 – Runs based on real observed historic data. Deterministic and stochastic methods

Run	B4	H1	H2	H3	Avg. H1:H3	HS	Observed fuel cell availability scenario
LFP battery	Yes	Yes	Yes	Yes	Yes	Yes	
MCFC	Yes	$X_{\omega 1}(t_0)$ = 8	$X_{\omega 2}(t_0)$ = 1	$X_{\omega 3}(t_0)$ = 4	Avg.	$t_{0\omega}$	
Total energy costs	$ 52 203	$ 68 878	$ 57 371	$ 60 018	$ 62 089	$ 62 372	
Time-Of-Use charges	$ 16 798	$ 26 749	$ 22 102	$ 21 247	$ 22 518	$ 26 837	ω_1
						$ 21 351	ω_2
						$ 21 821	ω_3
Power demand charges	$ 20 699	$ 41 407	$ 28 500	$ 30 094	$ 32 038	$ 41 567	ω_1
						$ 28 160	ω_2
						$ 30 968	ω_3
Utility purchases, kWh	184260	287623	242823	228781	243358	287125	ω_1
						233515	ω_2
						236492	ω_3
MCFC generation, kWh	107671	5340	49583	63550	49115	5340	ω_1

						58950	ω_2
						55973	ω_3
Average battery SOC, %	24.5	39.2	46.4	39.2	41.6	54.4	
Electricity from the battery, kWh	2353	7385	4666	4302	5451	4952	

Table 6 – Comparison runs. Deterministic and Stochastic results.

Run	C1	C2	C3	C4	C5	C6	C1 - C4	C2 - C5	C3 - C6
LFP battery schedule	Avg H1:H3	Avg H1:H3	Avg H1:H3	HS	HS	HS	Savings		
MCFC	$X_{\omega1}(0) = 8$	$X_{\omega2}(0) = 1$	$X_{\omega3}(0) = 4$	$X_{\omega1}(0) = 8$	$X_{\omega2}(0) = 1$	$X_{\omega3}(0) = 4$			
Total energy costs	$ 70 296	$ 59 017	$ 64 213	$ 69 126	$ 57 560	$ 60 431	$ 1 170	$ 1 457	$ 3 781
TOU charges	$ 26 807	$ 21 245	$ 23 232	$ 26 837	$ 21 351	$ 21 821	$ -29	$ -105	$ 1 411
Demand charges	$ 42 705	$ 29 596	$ 35 661	$ 41 567	$ 28 160	$ 30 968	$ 1 138	$ 1 435	$ 4 693
Average battery SOC	41.6%			54.4%					
Elec. from batt., kWh	5451			4952					

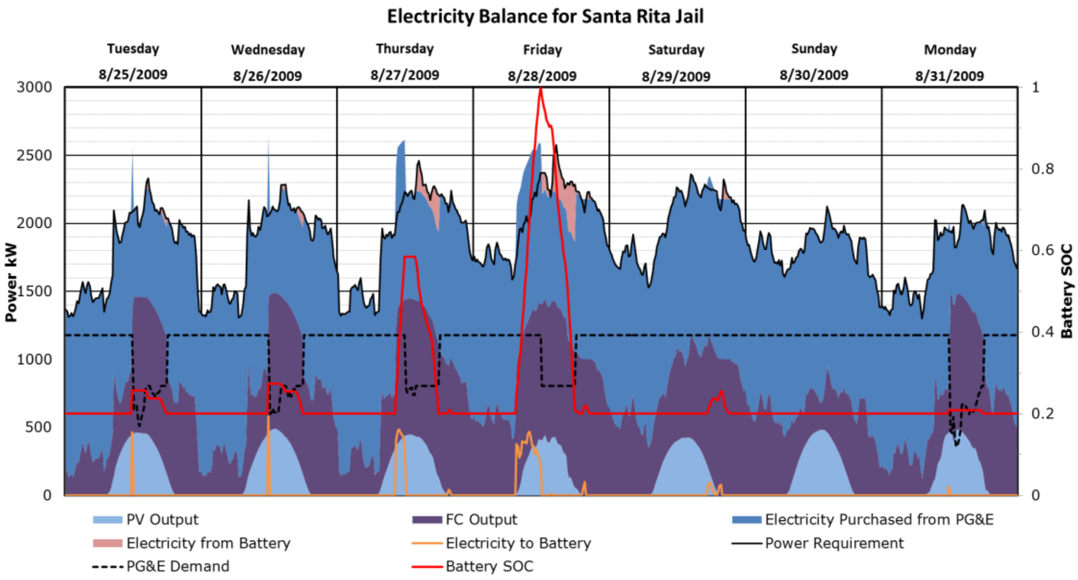

Fig. 1 – B4 run. Detailed scheduling.

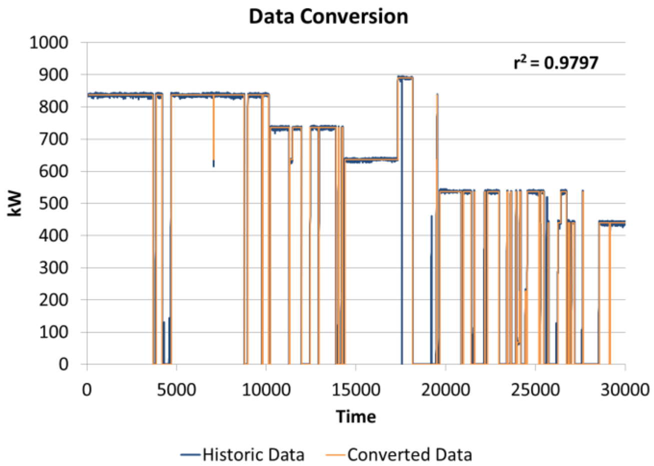

Figure 2 – Historic and filtered MCFC output data

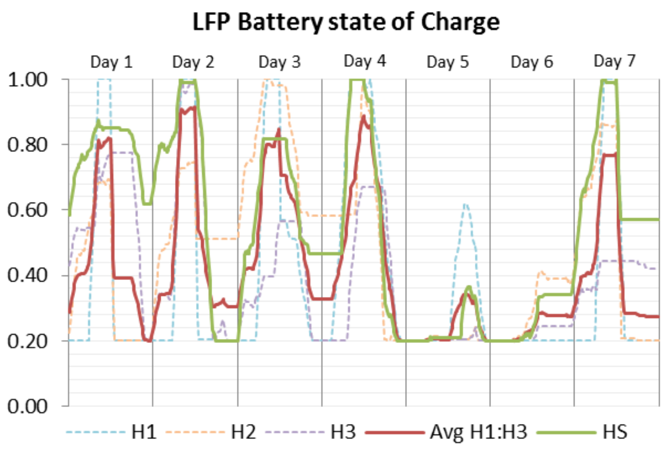

Figure 3 – LFP state of charge